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THE BACKGROUND OF THE MOST SUCCESSFUL VENTURE CAPITALISTS

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Abstract

This Work Project aims to conduct an exploratory analysis into whether and to which degree socioeconomic variables can predict Venture Capital performance. Using Crunchbase's database, tests were conducted to test for independence, both in the complete sample and in certain sub-samples. Gender, alma mater and academic field do not seem to be independent of VC performance, with a lower proportion of business majors and a higher proportion of MBAs, sciences majors and women in top VC firms. The notable exceptions being the sub-samples with the highest average age, where women are less likely to work on top firms.

Key Words: Venture Capital; Entrepreneurship

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Motivation

Venture capital, in loose terms, consists of the capital that is typically allocated towards investment in young firms with high potential for growth. The investors tend to have a large involvement in the companies' operations and usually seek an exit via sale or IPO (Metrick and Yasuda 2011).

Its effects in the economy have been extensively studied, with the some of the main findings being that it tends to be related with innovation in a "positive and significant" (Kortum and Lerner 2000) manner and that regions with a higher venture capital availability tend to have "raise[d] employment and aggregate income" (Samila and Sorenson 2011) levels. In the same vein, van Pottelsberghe & Romain (2004) found that "VC contributes to [economic] growth through two main channels": "the introduction of new products and processes on the market" and "the development of an improved absorptive capacity of the knowledge generated by private and public research institutions".

Venture capitalists often add more value-added than just the capital itself, and, as Kaplan & Schoar (2005) found, there is a strong level of inter-year persistence in the VC returns (at least the ones with good returns, due to the positive results-leaning selection bias in the data). Besides, due to the characteristics of the industry, namely the high asymmetry of information among players, reputation is the word of the day, with entrepreneurs often willing to forfeit some part of their valuation in order to work with the most reputable VCs (Hsu 2004).

There seems to be a significant difference in performance between the top VCs and the others. Some of it is certainly due to better deal sourcing (since the industry returns are very concentrated in a handful of investments), but little has been researched about factors involving the people who work in the top VC firms and the other ones. Little is known about whether there is a difference between the cultural and demographic variables of these firms' workers. Some attempts have been made, but, as Mindus & Wessel (2017) found, it is hard to get strong conclusions, as there are many factors to consider and it is hard to come by good data.

Additionally, there is already some research on the characteristics of successful entrepreneurs. Robinson & Sexton (1994), found that “higher levels of education increase both the probability of becoming self-employed and the success of individuals in that sector”.

This thesis will focus on analyzing some cultural and demographic variables of venture capitalists and studying if there are significant statistical differences between the better and worst-performing venture capitalists on these variables’ level, that is, figuring out if there’s statistical independence between the VC performance and these variables.

Literature Review

Since decision-making is an essential part of VC management, it is imperative to consider what might influence it. However, it is also important to search for context-specific factors that might affect performance. Since there is not much research on the mechanics behind these variables in a venture capital context, it is necessary to proceed with the assumption that success in the VC industry depends somewhat on decision-making ability.

Multiple research shows that the demographical characteristics of managers tend to affect decision making. Hambrick & Mason (1984) proposed the Upper Echelon theory, which states that “organizational outcomes - strategic choices and performance levels - are partially predicted by managerial background characteristics”. These characteristics include Socioeconomic Background, Formal Education, Group Heterogeneity, and Age, among others.

Education Level

Formal education level - the highest academic degree that an individual has attained - has been shown to influence effective decision making. It might influence management through a positive correlation between education level and openness to innovation (Kimberly and Evanisko 1981).

Klein (1999) has also shown that “the higher the academic degree, the higher the [methodological-statistical] ability in decision-making”, and that this improvement occurs across all areas of specialization. More studies have also indicated this link, namely Lehman & Nisbett's (1990) and Kim, Choi, Kim, & Pop-eleches' (2018), with the latter focusing specifically on economic rationality and decision-making. From the literature, it would be expected that education level and VC performance are not independent.

Age

Age is a variable that has also been shown to affect decision making. Research has both found that age can lead to better or worse decisions. Taylor (1975) wrote that “little evidence was found […] that older decision-makers tend to be less facile information processors” when compared to their younger peers. Child (1975) suggests that younger managers “can at their best achieve extremely favourable rates of company growth. Their worst is […] not generally inferior to the worst performance of companies with more elderly managements”. They also suggest that younger management might foster innovation in their companies.

On the other hand, Worthy, Gorlick, Pacheco, Schnyer, & Maddox (2011) found that participants of different ages fared better on different kind of tests, and suggested that “although aging may lead to some cognitive declines, it may also lead to gains in the insight and wisdom needed to make the best decisions”. These inconsistencies in results seem to indicate that age and VC performance are independent.

University Choice

The university that an individual goes to usually signals something about them. Some universities signal that the student had a good education and is likely a good professional, some that they were from a high net-worth family. In any case, it is important to understand that it ends up being a proxy for some factors other than the quality of education itself.

When it comes to socio-economic factors, historical analysis shows that Ivy League universities (some of the most well-respected and elitist North American academic institutions) have had a propensity to accept applications from students whose families are somehow connected to the university. As *The Guardian* (Gross 2019) reported, the acceptance rate for these students is 33%, when compared to a rate under 6% for others. In addition, many of these students tend to be already somewhat wealthy.

Even the constitution of students' families seems to influence admission rates. As Lillard & Gerner (1999) found, "students from disrupted families were less likely to apply to, be admitted to, attend, or ever attend a four-year college" and that these students were "also less likely to choose a selective college". Considering that the rates of divorce are already influenced by several socio-demographical factors (Kposowa 1998), it adds even more nuance to the background of students in top universities.

Curiously, some of the value of an education in these institutions has been attributed to signaling. This means that students from whichever schools they attend, independently of the quality of the education they end up getting, will be mostly judged based on their alma mater. Caplan (2018) estimates that up to 80% of the value added by a university is this signaling effect. Given their libertarian views and agenda, this value is likely inflated, however, it makes sense to consider this as a meaningful factor. This also seems to be the case, as the college one attends might matter quite a bit for predicting career success (Miller, Xu, and Mehrotra 2015).

With this in mind, it is clear why this is a variable worth studying in this context, with the caveat that, in actuality, the variables this one is a proxy to might be the more determinant ones.

Still, it seems likely that a higher proportion of VCs in top firms studied in the most prestigious universities, therefore, VC performance and attendance at a top university would not be independent.

Gender Diversity

Heterogeneity in management has been shown to correlate with more critical and creative thinking within groups, which might lead to better decision making (De Dreu and West 2001). Hambrick, Cho, & Chen (1996) found that "each type of heterogeneity contributed in its own way to overall […] performance" in a competitive environment. However, in a comprehensive literature review, Williams & O'Reilly III (1998) found that while diversity can have a positive influence in performance, it can also "impede group functioning" and hinder effective decision-making.

One such kind of diversity is gender-diversity, which is currently a hot topic in venture-capital. More specifically, both the financing of female-founded companies and the percentage of women working in venture capital. This seems to be an issue, as, in 2018, only 2.2% of all American VC investment (measuring by value) went to companies founded by women (Clark 2018). According to All Raise, an NGO focusing on decreasing the gender gap in the VC and entrepreneurship industries, "71% of venture firms still do not have a single female partner, and only 7% of firms have equal gender representation in their partnership" (2019).

It is also worth noting that many female managers tend to "feel excluded from informal relationships with their White male colleagues" (Morrison and Von Glinow 1990), which might become an issue in a field where, as stated before, success often depends on deal sourcing. Deloitte's (2019) survey on human capital in the VC industry also points in the same direction, with only 14% of investment partners being women (*n=589*) in 2018.

Little academic research has been done on the effects of gender-diversity on venture capital firms, and literature seems to predict that VC performance and gender diversity are not independent.

Academic Field

When it comes to the academic field of an individuals' effect on decision making, there are several factors to consider:

Firstly, there's the possibility that students who decide to pursue certain majors have some common personality traits (Germeijs et al. 2012). Balsamo, Lauriola, & Saggino (2012) and Kaufman, Pumaccahua, & Holt (2013) also found that certain personality types seem to influence students' decisions regarding their college major. Some of these characteristics might be more beneficial to decision making and overall good performance in a venture capital context than others.

In a similar vein, research shows that, in some situations, students' choice of university or field of study depends, to some degree on cultural values and parents' expectations (Leung et al. 2011). This points to the fact that this variable might be a proxy to some other ones, such as ethnicity or socio-economic background.

It is also important to notice that there might be value in diverse teams, as mentioned above, and some multidisciplinary teams are an example of just that.

Since there are many indications that the academic field might consistently reflect some of the students' characteristics, the literature predicts that VC performance and academic field are not independent.

Demographic Variables in Venture Capital

While Dimov & Shepherd's (2005) research on these variables in a venture capital context has led to interesting results, it suffers from a few limitations. Firstly, it uses a low sample size (*n=112*), and only focuses on senior managers at VC firms. This might overlook how other non-senior workers at the firms might affect the decision-making process and the contribution of their expertise in specific fields. It also focuses on the proportion of "home runs" and "strikeouts", the latter of which might not lead to relevant insights, as the proportion of bankruptcies in the firms' portfolio companies is relatively similar between the better and worse performing funds. This means that a lower proportion of bankruptcies might not equate to better performing funds since outstanding performance is in great part due to the "home runs".

Zarutkie (2010) has also made significant contributions to research in the area. Their study focused on the demographic variables of the top management team of first-time venture capital funds. Once more, it focuses solely on fund managers. Moreover, analyzing the managers' field of education and ignoring the support team's might lead to ignoring the effects of their expertise, while considering their contribution (when measuring the firms' performance). Additionally, it focuses on first-time funds, which might neglect the effects of organizational knowledge accumulation. Still, this is a great contribution to literature in the area.

Methodology and Data

In order to achieve the goal of the project, Crunchbase's investors dataset was used. The dataset was originally divided into several smaller ones. Four were used: *Organizations, Investors*, *Degrees*, and *People*. Most of the data about investors' personal life are added by users, possibly the investors themselves (this will be expanded upon on Limitations).

When it comes to the *Investors* and *Organizations* databases (which were merged into one), both individuals and organizations were listed. Since this thesis focuses on regular venture capital firms, the dataset was filtered by removing observations in the following way: 1) Individuals – effectively removing individual Angel Investors; 2) Organizations without name or country code; 3) Organizations whose main role was not "investor" - thus removing most accelerators and incubators, for example; 4) Organizations who did not include “venture capital” in their investor profile; 5) Organizations that were subsidiaries of corporates, thus excluding corporate venture capital firms - as they often have different goals than regular VCs (Maula, Autio, and Murray 2005); 6) Organizations which were classified as investment banks - as they tend to have a different profile than regular VCs.

Similarly, the Degrees and the People datasets were concatenated. In order to deal with missing data, the assumption that everyone in the industry had at least some college was made. Therefore, entries with no college were not considered as observations when analyzing these variables. In order to deal with multiple degrees, only the degree of the highest level was considered, along with the field of that degree. As an example, if an individual had a bachelor’s degree in Mathematics and a master’s on Law, the model would consider their study field as Law.

Once again, some assumptions had to be made, so as to clean the data. The relative position of the MBA in the higher education hierarchy was altered for the analysis’ sake (PhD > MBA > Master’s > Bachelor’s).

The study areas were divided into four fields – Sciences, Business, Law, and Others (the list of courses included in these categories is in Appendix A). Once more, since the model is not able to handle double majors in different areas, it gives prevalence to Law over Business and Sciences, Business over Sciences, and all these over Others. As an example, if someone has a degree in “Economics and Law”, it registers only as “Law”.

In order to estimate the age of the individuals, the average age for a Bachelor’s graduate in the USA was used (OECD 2016), 22. For that, the following formula was used:

$$Age = 2019 - Graduation\ Year + Average\ Age\ on\ Graduation$$

One of the main challenges of this thesis is defining who exactly are the “Top VCs”. Since there are not enough undisclosed data to calculate the VC firms’ average Internal Rate of Return throughout the years, all the subsequent analysis will be conducted for three different criteria: 1) List of best VC firms as chosen by VCs (CB Insights 2016); 2) VC firms with more exits; 3) VC firms with more investments.

These lists consist of 20 firms as to keep consistency amongst them, and there is some overlap of the firms included in them. None of these are perfect measures of VC performance, but all of them point to success and consistency, which is important in the industry. The firms included in each list are represented in Appendix B.

To select the best universities, the *U.S. News* 2020 National University Rankings (2019) was used. This ranking only takes into consideration North American universities, selecting them based on multiple criteria, such as expert ratings, social mobility, faculty resources, and outcomes – such as “[the universities’] success at retaining and graduating students within 150% of normal time (six years)” (U.S. News 2019).

This ranking was selected since its results have been shown to influence both the applicants’ and the universities’ behavior. Monks & Ehrenberg (1999) have shown that “an increase in a selective private institution’s US. News rank (a move to a less favorable ranking) leads the institution to accept a greater percentage of its applicants (an increase in its admit rate); that a smaller percentage of its admitted pool of applicants then matriculates (a decrease in its yield); and that its resulting entering class is of lower quality, as measured by average SAT scores”. Although this is not a perfect proxy for the quality of a university – it has numerous limitations, such as “does not reward institutions for [collaborating with each other]”, the fact that “the USNWR ranking methodology provides incentives for institutions to take actions that are not always socially desirable" (Ehrenberg 2003), and the absence of non-American universities – it is a relevant one, and so it was used.

Since the best universities list only considers the American academic context, it is logical that some of the variables might be somewhat biased towards Americans. Even though all the firms that were considered the best were American, this might still prove to be a problem. As an example, the proportion of individuals that went to the universities that were considered and that are not working on the top firms might be very different for the USA and the rest of the world. Thus, analyzing while grouping both the American and non-American VCs might lead to some limitations on the conclusions. This is especially a problem because it might be demographical differences between the USA (where all the top VC firms are headquartered) and the rest of the world driving the significance of the results, which would lead to wrong conclusions.

For Age, the hypotheses are:

$$H_0: \mu_{Top\ VCs} = \mu_{Other\ VCs} \quad H_1: \mu_{Top\ VCs} \neq \mu_{Other\ VCs}$$

For the other variables, the hypotheses are:

$$H_0: The\ variables\ are\ independent. \quad H_1: The\ variables\ are\ not\ independent.$$

Results and Discussion

Descriptive Statistics

Firstly, some descriptive statistics of the whole VC population for the studied variables were gathered (*Appendix C*). Clearly, there are some differences in the values when considering the North American and the Global context, especially when it comes to academic level (some of it might be due to differences in the American and European definitions of Masters' and Bachelors'). Still, little difference is observed in the gender diversity and academic field.

Results and Discussion

All the following results refer to the North American observations, for the aforementioned reasons. In order to determine the statistical significance of the findings (except for Age), Pearson's Chi-Square test was used. While this test gives the probability that the studied variables are independent, it does not give insights into the relationship between them. The test used to measure the strength of the relationships was Cramér's V. All the variables are compliant with the assumptions in order to conduct these tests (Mchugh 2013), except for Academic Field when using the number of exits as criteria (as the expected value of Law graduates in top-VCs is less than 1). Still, the test was conducted for that case, with the caveat that the interpretation might be slightly flawed due to that.

Afterwards, Probit regressions were applied to the data, firstly on a larger level, taking into consideration all the independent variables as inputs, and secondly, in order to dig deeper into the data, the regressions were applied to sections of the dataset, keeping one of the variables constant. "Law" was aggregated into "Others" due to its small sample size.

Age

When it comes to age, after performing an analysis of variance (ANOVA), it was found that, for any of the different considered criteria, the null hypothesis that the average age was the same for the different VC categories was not rejected, for any relevant significance level. This is not surprising since the literature was not consistent in predicting performance through age.

The assumptions for the ANOVA were tested and the results show that the assumptions remain valid. Barlett's Test P-Value took values between 0.17 to 0.30, so the null hypothesis that there is homoscedasticity is not rejected for any reasonable significance level. When using the Shapiro-Wilk's test, the null hypothesis that the residuals are normally distributed is rejected, with P-Values in the [0.00 – 0.05] range, for most relevant significance levels. Still, as the distributions of the residuals clearly resemble a *bell curve* for all groups and criteria (see Appendix D), and since we can use the central limit theorem (*n = 1874*), this assumption decreases in its importance, as the F-test is robust to these deviations (Lix, Keselman, and Keselman 1996; Blanca et al. 2017). Therefore, the test can still be valid, even if its output has a slight bias.

Table 1 – Age Analysis of Variance Table

	List	Exits	Investments
Top VCs Average (Years)	45.93	46.43	45.98
Non-Top VCs Average (Years)	47.10	47.06	47.12
Top VCs Standard Deviation	11.03	11.24	11.32
Non-Top VCs Standard Deviation	11.98	11.98	11.97
Barlett's Test P-Value	0.17	0.27	0.30
F-Statistic	1.44	0.44	1.59
P-Value	0.23	0.51	0.21

n = 1874

Academic Level

The null hypothesis that the performance of VCs is independent of the level of education is only rejected when analyzing the data with the Investments criteria (*P-Value: 0.024*), for a significance level of 97.5%.

Table 2 - Academic Level Contingency Table

		List		Exits		Investments	
		Top	Non-Top	Top	Non-Top	Top	Non-Top
Conditional Frequency	PhD	6.5%	6.7%	5.0%	6.9%	5.1%	6.9%
	MBA	40.6%	45.7%	45.5%	45.3%	41.0%	45.7%
	Ms	10.2%	8.2%	8.9%	8.3%	10.1%	8.2%
	Bs	42.7%	39.4%	40.6%	39.6%	43.8%	39.2%
Critical Value (χ^2)		5.21		2.84		9.38	
Cramér's V		0.03		0.02		0.04	
P-Value		0.16		0.42		0.02	

n = 5738

This difference in results is likely due to the differences in the hiring policy for each firm that is considered a top-VC. Since the data are not consistent amongst the criteria, it would be wrong to generalize any single conclusion. This seems to contradict the literature, as a higher educational level in workers does not translate to a higher VC performance.

Academic Field

Regarding the academic field, for all the criteria, the null hypothesis that the field and VC performance is independent is rejected, for a significance level of 97.5%. This might be in line with the literature, that predicted that there are differences between students from different fields. In all the cases, top-VCs have a larger proportion of Sciences graduates, which comes at an expense of Management graduates, and, more significantly, graduates for "other" fields (which includes most Social Sciences and Liberal Arts majors). Cramér's V was measured in the [0.04 – 0.08] range, which implies a weak relationship between the variables (Akoglu 2018). It is worth noting that weak relationships are expected when the variables depend on more than one factor (Mchugh 2013), as happens in this case, since it is not expected that the VC performance is dependent solely on the academic field.

Table 3 - Academic Field Contingency Table

		List		Exits		Investments	
		Top	Non-Top	Top	Non-Top	Top	Non-Top
Conditional Frequency	Sciences	19.6%	11.0%	15.5%	11.3%	17.8%	11.0%
	Management	58.4%	64.1%	63.6%	63.6%	60.6%	64.0%
	Law	0.2%	0.2%	0.2%	0.2%	0.4%	0.1%
	Other	21.7%	24.8%	20.7%	24.9%	21.2%	24.9%
Critical Value (χ^2)		29.38		10.52		24.69	
Cramér's V		0.07		0.04		0.07	
P-Value		0.00		0.01		0.00	

n = 5738

A possible interpretation of these results that tech-literate VCs have the upper hand in performance. This might make sense as they could be better equipped to evaluate and provide better guidance to technological startups.

It is also possible that this is due to a larger concentration of successful entrepreneurs - who tend to come from STEM fields (Wadhwa, Freeman, and Rissing 2010) - in the best VC firms' ranks. Anecdotal evidence might point to this, with Bill Trenchard (co-founder of Liveops) and Sean Parker (co-founder of Napster) working at First Round and Founders Fund respectively.

University Choice

Similarly, the null hypothesis that the university group and the VC performance were independent was rejected with a significance level of 97.5%, for all the criteria. In every case, in the top-VC group, more than 60% of workers had studied in one of the 20 best North American colleges. For all lists, Cramér's V measured in the [0.06 – 0.08] range, which equates to a very weak to weak relationship between the variables (Akoglu 2018).

Table 4 – University Choice Contingency Table

		List		Exits		Investments	
		Top	Non-Top	Top	Non-Top	Top	Non-Top
Conditional Frequency	Top Uni	61.0%	49.0%	61.4%	48.8%	60.6%	48.7%
	Non-Top Uni	39.0%	51.0%	38.6%	51.2%	39.4%	51.3%
Critical Value (χ^2)		23.05		29.44		27.87	
Cramér's V		0.06		0.07		0.07	
P-Value		0.00		0.00		0.00	

n = 5738

This value might be due to quite some effects. On the one hand, these are generally considered to be great universities, so it might just be that a large proportion of the best performers studied there. On the other hand, it is also important to think about the signaling effect that these universities provide. When it is considered that there is a small number of jobs in the industry for the number of applicants (Moules 2017), it might be the case that the interviewers give privilege to those coming from these prestigious schools.

It might also be that this is due to a self-replication mechanism in these firms' hiring policy - *homosocial reproduction* (Elliott and Smith 2004). This might happen either due to the universities themselves or due to other conditions that the applicants might have, such as socio-economical background (Rivera 2012). In other words, the interviewers might be inclined to give the jobs to people they identify with in one way or another. Since this is a somewhat elitist setting, and many of the interviewers already come from these schools (and, presumably, from a privileged background, when it comes to wealth), they might have a tendency to hire similar people, either on purpose or otherwise.

Gender

Regarding gender, for two of the considered criteria, the null hypothesis that gender and VC performance were independent was rejected with a significance level of 97.5%. While the same didn't happen when we chose the top-VCs based on the number of exits (*P-Value: 0.06*), even in this case, the proportion of females in the category was still larger than in the others category (*23.3% vs. 20.6%*). Cramér's V measured in the [0.01 – 0.05], which implies a weak strength of the relationship between the variables (Akoglu 2018).

Table 5 – Gender Contingency Table

		List		Exits		Investments	
		Top	Non-Top	Top	Non-Top	Top	Non-Top
Conditional Frequency	Male	70.9%	79.7.0%	76.7%	79.4%	73.1%	79.7%
	Female	29.1%	20.3%	23.3%	20.6%	26.9%	20.3%
Critical Value (χ^2)		35.45		3.61		24.65	
Cramér's V		0.05		0.02		0.04	
P-Value		0.00		0.06		0.00	

n = 15142

This seems to reinforce the literature's prediction that there is value in diversity. It, however, adds an interesting counterpoint to the *homosocial reproduction* hypothesis raised above. Still, it is worth noting that there can be many similarities between male and female workers when looking beyond gender. If these characteristics were to be behind the hiring decisions, the homosocial reproduction process might still be taking place, even if it is fostering gender diversity.

Probit Analyses

Table 6 – Probit Results for All the Variables

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.16	0.12	0.10	-0.24	0.02	0.10	-0.15	0.13	0.10
	PhD	-0.12	0.59	0.22	-0.21	0.40	0.24	-0.11	0.62	0.22
	MBA	-0.18	0.13	0.12	0.44	0.00	0.12	0.22	0.04	0.11
	Ms	0.00	1.00	0.17	0.13	0.45	0.17	0.15	0.36	0.16
	Management	-0.37	0.00	0.11	-0.37	0.00	0.12	-0.34	0.00	0.11
	Sciences	0.19	0.12	0.12	0.14	0.27	0.13	0.18	0.14	0.12
	Top University	0.14	0.10	0.08	0.13	0.13	0.08	0.14	0.09	0.08
	Age	-0.02	0.00	0.00	-0.02	0.00	0.00	-0.02	0.00	0.00

n = 1873

When analyzing the holistic model, only a worker's age and them having a Management degree are variables that are statistically significant for all three criteria, for a significance level of 95%, both with a negative coefficient. In addition, being male leads to a significant negative coefficient for the Exits criterion, and the highest academic degree being an MBA has a positive, significant coefficient for both the Exits and Investment criteria. While not statistically significant, coming from a sciences background or a top university also have positive coefficients and relatively low p-values and, therefore, small confidence intervals, similarly to what was seen on the Chi-Squared tests.

When splitting the sample into three different age groups (see *Appendix E*) - age ≤ 35 ; 35 < age ≤ 55 ; age > 55 - it is clear that, for the younger ones, only age has a significant, negative, coefficient through all the criteria, as it does for all groups. Having a masters' degree also seems to increase the marginal probability of being a top VC, even if only statistically significant when using the List as a criterion, with a large coefficient. For the middle bracket, having a science degree or coming from a top university are both significant variables, both with positive coefficients. As for the older bracket, the only significant variable, aside from age, is coming from a top university, which has a positive coefficient and is significant for both the List and Investments criteria. When looking at the coefficients independently of their P-Values, it is noticeable that, for the eldest sub-sample, the coefficient of being a man is positive, while the opposite happens for the younger groups. This might hint at some historical gender discrimination in the field. As for sciences having a positive coefficient in the younger groups, it might be a reflection of the technology focus of the industry in the past decades. As was speculated above, individuals from a sciences background might be more likely to be successful in the field. As for the Top University variable having a negative coefficient in the younger sub-sample, it might suggest that the field, known for being elitist, might be changing. It might also be that recruiters in the top firms are evaluating job candidates in a different way than before, focusing more on personal characteristics and experience than on academic background.

When dividing the sample into two different groups based on gender, it becomes clear that the situation is, in fact, different for men and women in the industry. For men, being a management graduate decreases one's marginal probability of working in the top firms, with a significant negative coefficient for all criteria. On the other hand, having an MBA increases that probability, being statistically significant for two of the three criteria, while still having a low P-Value for the List criteria (0.06). For women, only Age is significant, while management has a positive coefficient. This might be indicative of recruiters having different expectations for men and women, or even hiring different genders for different positions within their firms. Similarly, even if not significant, for all criteria, women’s Top University coefficient is larger than men’s, which might point to a greater importance of the signaling effect that comes from the Alma Mater for women.

For management graduates, being a man decreases the probability of being a top VC. Having an MBA and coming from a Top University have positive, significant coefficients for some of the criteria, though not all. For science students and graduates from other majors only age is significant.

For PhDs and MBAs, only age is significant. For Masters, being a man has a positive, significant coefficient for the Investments criterion, as well as age, albeit negative, for all criteria. As for Bachelors, Management, being a man, and age have a negative, significant coefficient for all criteria. The male coefficient for PhDs and Masters might once more be related to gender discrimination in older generations, as the average age for the sub-samples are, respectively, 49.9 and 51.7, both older than the average age for the full sample, 47.0.

For graduates from Top Universities, only age has a significant coefficient for all criteria, though Male has a negative one and MBA a positive one for the Exits criterion, Management has a negative one for both the Lists and Exits criteria. Regarding the graduates from other schools, being a management major leads to a significantly lower probability of being a Top VC, as well as being marginally older.

Some more Probit regressions were calculated for sub-samples created by the interception of others (e.g. women with Bachelors’, MBAs from Top Universities). For the most part, these regressions yielded no statistically significant results, with the coefficients having large confidence intervals, making them borderline impossible to interpret. Most of the interpretable ones do not reveal relationships that were not apparent in the bigger samples. Since these samples were more specific than the previous ones, it is likely that the reduction of sample size drove the inconclusive results. Still, it is interesting how negative was the male coefficient for management bachelors, which suggests this is one of the main drivers of the negative male coefficient in the general sample.

Some of these results seem to contradict the literature, though it is important to understand that this is not necessarily happening. Some of the results that were observed in the Chi-Squared tests were not observed in these regressions. This does not mean that these variables do not influence the dependent one, but that the coefficients, in this model, are not significant. This might mean that a better model (as this one might not describe reality well) or more data might be necessary.

Conclusions

From the results, it can be concluded that gender, academic field, and the alma mater are not independent of VC performance. It can also be concluded that the mechanisms through which the studied variables interact with VC performance are different for different cases, hinting that this is a complex topic that should be studied further, possibly by increasing sample size or focusing on more variables.

Moreover, even if not always statistically significant, for the most part, women seem to have a higher probability of getting into the Top VCs. This might be due to either women being more suited for the job, positive discrimination within the top firms, or even the possibility that the field actively discriminates against women, and the few that managed to break into the field were actually some of the best performers, thus making it into the best firms. Curiously, the sub-sample in which the observations are over 55 is one of the few where being has a positive coefficient (even if not statistically significant). This might also point to some degree of gender discrimination in older generations in the field.

Another interesting result is that, overall - especially for men - coming from a management degree decreases the probability of being a Top VC. This was consistent for both types of tests. Having an MBA, counterintuitively, increases the probability for almost all cases. This might be due to the MBA being a professional degree with students from different academic backgrounds. So, it is still possible that the ones most likely to be successful are those with a technical background, as speculated above.

It is neither surprising nor concerning that some of the findings seem to contradict the literature since the literature was not focused on the venture capital industry and there is little, if any, empirical evidence that the performance and decision-making abilities that are measured in the cited works are important for success in the VC industry. This also proves to be a thread that can be picked up for future research into the topic.

Lastly, this work helps to shed light on the VC industry. While the results were satisfactory, and patterns were found among the variables that predict VC performance, it is important to realize that these variables do not explain VC performance by themselves. As this is a relatively small field, individual characteristics, personality and experience are likely to be the biggest drivers of success, even if some of it can be predicted through the studied variables.

Limitations

Although this work successfully manages to analyze the industry, it nevertheless suffers from some limitations.

Firstly, there’s the issue of the data themselves. Most of the data is self-reported (Dalle, Den Besten, and Menon 2017). Not only might this give rise to the problem that some of it might be inaccurate – either by accident or design - it might also suffer from selection bias. Which is to say that some specific subsets of VCs (e.g. worse performing ones, or those not living in San Francisco) might have an inclination, for whichever reason, to not fill in their data as much as the other ones. This would lead to a misrepresentation of the population. This seems to be happening, since the proportion of top VCs, when considering the ones that have information about their academic degrees (for global data, using the number of exits as a criteria), is double than when considering the ones that just have information about their gender (*6.2%* vs. *3.1%*). This seems to point to the possibility that worse-performing VCs tend to have less information about them on the Crunchbase database than the best ones.

Another problem that this thesis might be incurring in is a wrong distinction between the study fields. This distinction might be neither academically nor practically relevant. The list is not comprehensive when it comes to the majors included in each field and is somewhat arbitrary in its separation. Similarly, the fact that the analysis method does not consider double majors nor academic degrees in different fields, and the way the model considers the MBA to be "above" other master's degrees, might lead to biases in the results.

It also might be happening that, due to the size of the data and due to only considering 20 firms as the best ones, the internal organization and hiring policy of each firm might have a large impact on the results.

Most importantly is the fact that generalizations are very hard to make through these data. This analysis concerns industry-level data, not company-level. This means that there is no information about these variables within each firm. There are not many conclusions here that could be used to decide on the best way to organize a VC firm. As far as this work is concerned, some of these firms might only hire Ivy-League graduates and another one might only hire from the University of Phoenix.

Appendices

Appendix A

Table 7 – List of keywords considered for each field

Field	Included Keywords
Sciences	"CS", "Engineering", "Mechanical", "Computer Science", "Technology", "Statistics", "Math", "Biology", "Programming", "Technology", "Physics"
Management	"Management", "MBA", "Business", "Finance", "Economics", "Accounting", "Administration", "Marketing"
Law	“Law”

Appendix B

Table 8 – List of firms considered for each list

List	Included Firms
Best VCs List	Accel, Andreessen Horowitz, Benchmark, Bessemer Venture Partners, Emergence, FLOODGATE, First Round Capital, Founders Fund, Foundry Group, Greylock Partners, Index Ventures, Khosla Ventures, Kleiner Perkins, Lightspeed Venture Partners, Lowercase Capital, New Enterprise Associates, Social Capital, True Ventures, Union Square Ventures, Sequoia Capital
Most Exits	500 Startups, Accel, Atlas Venture, Battery Ventures, Benchmark, Bessemer Venture Partners, CRV, DFJ, First Round Capital, Greylock Partners, Index Ventures, Kleiner Perkins, Lightspeed Venture Partners, Menlo Ventures, New Enterprise Associates, Norwest Venture Partners, Redpoint, Sequoia Capital, U.S. Venture Partners (USVP), Venrock
Most Investments	500 Startups, Accel, Andreessen Horowitz, Atlas Venture, Battery Ventures, Benchmark, Bessemer Venture Partners, CRV, DFJ, First Round Capital, General Catalyst, Greylock Partners, Index Ventures, Khosla Ventures, Kleiner Perkins, Lightspeed Venture Partners, Menlo Ventures, New Enterprise Associates, Norwest Venture Partners, Redpoint, SOSV, Sequoia Capital

Appendix C

Table 9 - Academic Level

		PhD	MBA	Ms	Bs
Absolute Frequency *(Relative Frequency)*	Worldwide	660 *(8.1%)*	3657 *(44.8%)*	958 *(11.7%)*	2890 *(35.4%)*
	USA	385 *(6.7%)*	2598 *(45.3%)*	479 *(8.3%)*	2276 *(39.7%)*

Table 10 - Academic Field

		Sciences	Management	Law	Other
Absolute Frequency *(Relative Frequency)*	Worldwide	974 *(11.9%)*	5191 *(63.6%)*	27 *(0.3%)*	1973 *(24.2%)*
	USA	668 *(11.6%)*	3652 *(63.6%)*	9 *(0.2%)*	1409 *(24.6%)*

n = 5738 for North American observations
n = 8165 for Worldwide observations

Table 11 - Gender

		Male	Female
Absolute Frequency *(Relative Frequency)*	Worldwide	22084 *(79.3%)*	5765 *(20.7%)*
	USA	11995 *(79.2%)*	3147 *(20.8%)*

n = 15142 for North American observations
n = 27849 for Worldwide observations

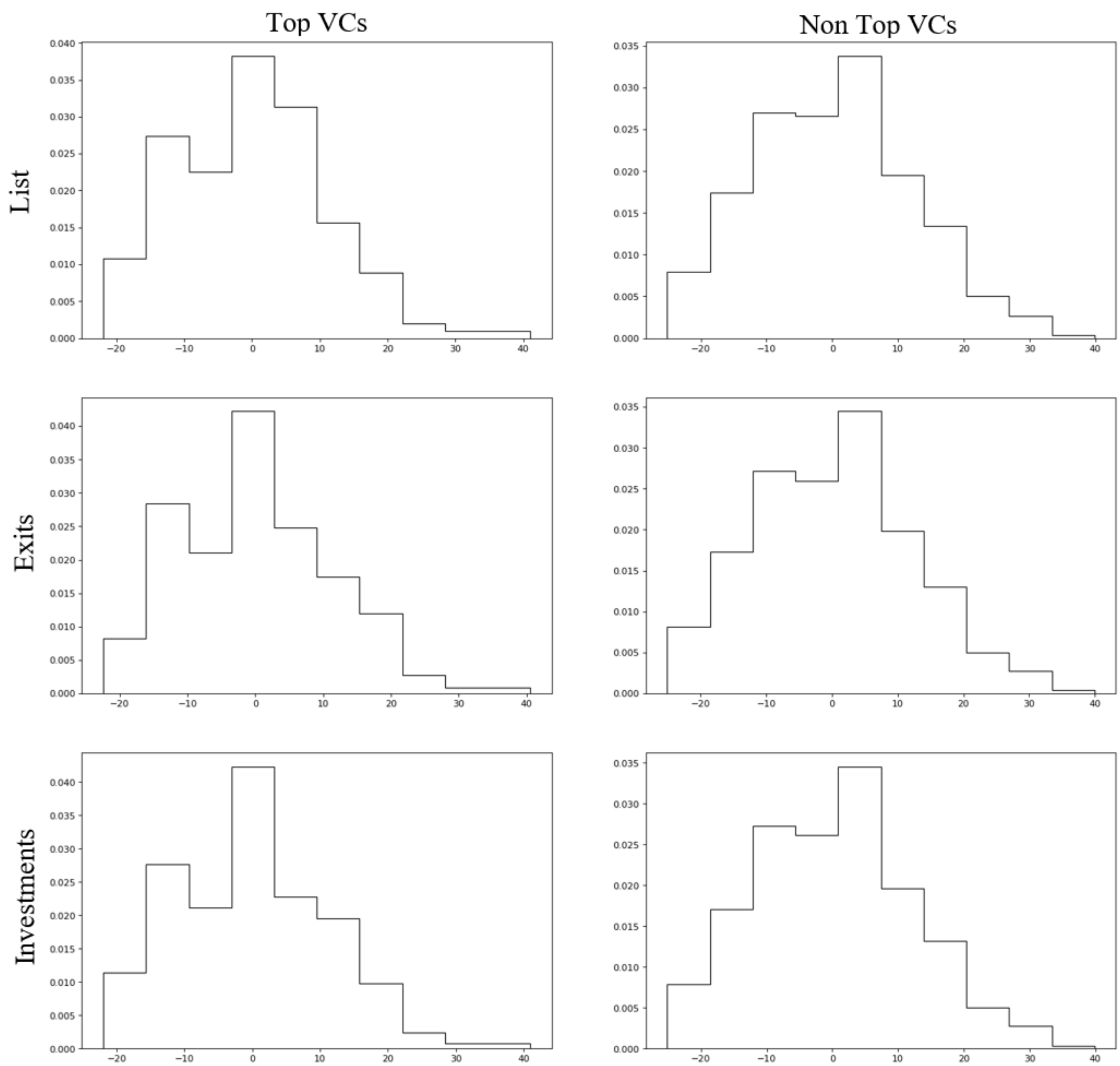
Table 12 – Average Age (years)

Worldwide	USA
46.45	47.00

n = 1874 for North American observations
n = 2289 for Worldwide observations

Appendix D

Figure 1 - Histogram of Residuals of the Distribution of Age for the Three Criteria



Appendix E

Table 13 – Probit Results for Age ≤ 35

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.31	0.12	0.20	-0.20	0.31	0.20	-0.12	0.53	0.19
	PhD	-4.41	1.00	980.74	-3.66	0.98	179.13	-3.94	0.99	277.82
	MBA	0.39	0.15	0.27	0.14	0.61	0.27	0.19	0.42	0.24
	Ms	0.81	0.02	0.35	0.64	0.09	0.37	0.49	0.18	0.37
	Management	-0.06	0.82	0.25	-0.03	0.89	0.23	0.08	0.71	0.22
	Sciences	0.32	0.28	0.29	0.05	0.87	0.30	0.10	0.74	0.29
	Top University	-0.16	0.39	0.19	-0.15	0.42	0.18	-0.09	0.61	0.17
	Age	-0.04	0.00	0.01	-0.04	0.00	0.01	-0.04	0.00	0.01

n = 371

Table 14 – Probit Results for 35 < Age ≤ 55

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.04	0.77	0.15	-0.21	0.16	0.15	-0.09	0.54	0.15
	PhD	-0.26	0.33	0.27	-0.54	0.10	0.33	-0.19	0.46	0.27
	MBA	-0.04	0.80	0.16	0.33	0.04	0.17	0.22	0.19	0.16
	Ms	-0.21	0.37	0.24	-0.09	0.70	0.25	0.00	1.00	0.22
	Management	-0.14	0.40	0.17	-0.11	0.57	0.19	-0.26	0.15	0.18
	Sciences	0.54	0.00	0.17	0.59	0.00	0.19	0.61	0.00	0.17
	Top University	0.36	0.00	0.12	0.40	0.00	0.12	0.34	0.00	0.12
	Age	-0.03	0.00	0.00	-0.03	0.00	0.00	-0.03	0.00	0.00

n = 1060

Table 15 – Probit Results for Age > 55

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	0.43	0.28	0.40	0.22	0.51	0.33	0.34	0.31	0.34
	PhD	-0.20	0.69	0.51	0.19	0.65	0.43	-0.34	0.51	0.51
	MBA	-0.16	0.58	0.29	0.33	0.24	0.29	-0.10	0.71	0.26
	Ms	-0.43	0.36	0.47	0.13	0.70	0.35	0.15	0.65	0.32
	Management	-0.22	0.45	0.29	-0.33	0.26	0.29	-0.19	0.47	0.26
	Sciences	-0.22	0.48	0.31	-0.09	0.75	0.29	-0.21	0.44	0.28

	Top University	0.42	0.05	0.21	0.30	0.12	0.19	0.41	0.03	0.19
	Age	-0.03	0.00	0.01	-0.03	0.00	0.01	-0.03	0.00	0.01

n = 442

Table 16 – Probit Results for Males

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	PhD	-0.09	0.73	0.25	-0.04	0.88	0.26	0.04	0.86	0.23
	MBA	0.24	0.06	0.13	0.51	0.00	0.13	0.28	0.02	0.12
	Ms	0.11	0.57	0.18	0.27	0.14	0.18	0.28	0.11	0.17
	Management	-0.49	0.00	0.12	-0.51	0.00	0.13	-0.46	0.00	0.12
	Sciences	0.12	0.36	0.13	0.03	0.85	0.14	0.09	0.47	0.13
	Top University	0.11	0.25	0.09	0.07	0.43	0.09	0.12	0.16	0.09
	Age	-0.03	0.00	0.00	-0.03	0.00	0.00	-0.02	0.00	0.00

n = 1562

Table 17 – Probit Results for Females

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	PhD	-0.05	0.93	0.55	-5.04	1.00	2036.18	-3.78	0.97	90.66
	MBA	-0.07	0.81	0.29	0.31	0.24	0.26	0.05	0.85	0.26
	Management	0.05	0.84	0.26	0.05	0.85	0.27	0.10	0.68	0.25
	Sciences	0.17	0.60	0.33	0.24	0.49	0.34	0.16	0.64	0.34
	Top University	0.23	0.29	0.21	0.30	0.14	0.20	0.13	0.52	0.20
	Age	-0.04	0.00	0.01	-0.04	0.00	0.01	-0.03	0.00	0.01

n = 311

Ms was discarded as the Standard Error is very large, and there are sign that quasi-separation might be happening.

Table 18 – Probit Results for Management

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
I	Male	-0.26	0.05	0.13	-0.37	0.00	0.13	-0.30	0.02	0.13

PhD	0.69	0.32	0.69	-3.85	0.99	224.67	-4.46	1.00	812.76
MBA	0.07	0.59	0.13	0.25	0.04	0.12	0.05	0.69	0.12
Ms	0.14	0.67	0.33	-0.51	0.28	0.47	-0.61	0.20	0.47
Top University	0.17	0.15	0.12	0.18	0.10	0.11	0.22	0.05	0.11
Age	-0.03	0.00	0.00	-0.03	0.00	0.00	-0.03	0.00	0.00

n = 1160

Table 19 – Probit Results for Sciences

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	0.01	0.97	0.26	-0.25	0.35	0.26	-0.04	0.88	0.25
	PhD	-0.15	0.60	0.29	-0.14	0.65	0.30	0.06	0.83	0.27
	Ms	0.12	0.60	0.24	0.34	0.15	0.24	0.31	0.17	0.23
	Top University	0.17	0.35	0.19	0.18	0.35	0.19	0.12	0.52	0.18
	Age	-0.02	0.00	0.01	-0.02	0.00	0.01	-0.02	0.00	0.01

n = 277

Table 20 – Probit Results for Other Majors

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.22	0.27	0.20	-0.15	0.45	0.20	-0.07	0.72	0.19
	PhD	-0.22	0.62	0.45	-0.07	0.87	0.45	-0.26	0.57	0.45
	Top University	0.00	1.00	0.17	-0.13	0.47	0.18	-0.09	0.59	0.16
	Age	-0.03	0.00	0.00	-0.03	0.00	0.00	-0.03	0.00	0.00

n = 436

Table 21 – Probit Results for PhD

	List	Exits	Investments

		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	0.14	0.81	0.60	0.46	0.51	0.70	0.61	0.36	0.68
	Management	0.71	0.37	0.79	-4.86	1.00	1401.49	-4.25	1.00	746.66
	Sciences	0.10	0.83	0.47	-0.08	0.86	0.46	0.20	0.66	0.45
	Top University	0.64	0.27	0.58	-0.40	0.40	0.48	0.41	0.46	0.55
	Age	-0.04	0.01	0.01	-0.03	0.03	0.01	-0.04	0.00	0.01

n = 70

Table 22 – Probit Results for MBA

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.06	0.74	0.19	-0.29	0.09	0.17	-0.18	0.30	0.17
	Top University	0.18	0.24	0.15	0.22	0.11	0.14	0.16	0.27	0.14
	Age	-0.03	0.00	0.00	-0.02	0.00	0.00	-0.03	0.00	0.00

n = 687

Table 23 – Probit Results for Masters' (Ms)

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	0.71	0.23	0.59	0.83	0.16	0.60	1.16	0.05	0.60
	Management	0.30	0.59	0.55	-0.96	0.10	0.59	-1.30	0.03	0.59
	Sciences	0.80	0.13	0.53	0.17	0.66	0.39	-0.02	0.95	0.36
	Top University	0.01	0.99	0.35	0.25	0.46	0.34	0.20	0.53	0.31
	Age	-0.05	0.00	0.01	-0.04	0.00	0.01	-0.04	0.00	0.01

n = 117

Table 24 – Probit Results for Bachelors' (Bs)

	List			Exits			Investments		
	Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error

Independent Variables	Male	-0.31	0.02	0.13	-0.33	0.02	0.13	-0.28	0.03	0.13
	Management	-0.38	0.00	0.12	-0.24	0.05	0.12	-0.23	0.05	0.12
	Sciences	0.17	0.22	0.14	0.16	0.29	0.15	0.17	0.22	0.14
	Top University	0.07	0.50	0.11	0.03	0.82	0.11	0.06	0.56	0.10
	Age	-0.02	0.00	0.00	-0.02	0.00	0.00	-0.02	0.00	0.00

n = 999

Table 25 – Probit Results for Top University Observations

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.21	0.12	0.14	-0.35	0.01	0.13	-0.19	0.14	0.13
	PhD	-0.08	0.75	0.25	-0.31	0.27	0.28	-0.01	0.96	0.24
	MBA	0.13	0.41	0.16	0.46	0.01	0.16	0.13	0.37	0.15
	Ms	-0.07	0.76	0.24	0.18	0.42	0.23	0.19	0.37	0.22
	Management	-0.34	0.04	0.16	-0.35	0.04	0.17	-0.23	0.14	0.15
	Sciences	0.22	0.19	0.17	0.22	0.19	0.17	0.20	0.23	0.16
	Age	-0.02	0.00	0.00	-0.02	0.00	0.00	-0.02	0.00	0.00

n = 999

Table 26 – Probit Results for Non-Top University Observations

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.10	0.52	0.16	-0.09	0.56	0.16	-0.09	0.53	0.15
	PhD	-5.12	1.00	3155.74	-0.06	0.91	0.51	-4.20	0.98	206.41
	MBA	0.08	0.69	0.19	0.26	0.15	0.18	0.17	0.34	0.18
	Ms	0.06	0.81	0.26	0.00	0.99	0.28	0.07	0.77	0.25
	Management	-0.35	0.03	0.16	-0.35	0.03	0.16	-0.39	0.01	0.15
	Sciences	0.21	0.27	0.19	0.06	0.77	0.20	0.18	0.31	0.18
	Age	-0.03	0.00	0.00	-0.03	0.00	0.00	-0.03	0.00	0.00

n = 874

Table 27 – Probit Results for Management Bachelors' Observations

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.5128	0.519	0.203	-0.45	0.03	0.20	-0.46	0.02	0.19
	Top University	0.1488	0.848	0.178	0.09	0.62	0.18	0.26	0.12	0.17
	Age	-0.0261	0.001	0.004	-0.03	0.00	0.01	-0.03	0.00	0.00

n = 438

Table 28 – Probit Results for Sciences Bachelors' Observations

		List			Exits			Investments		
		Coef	P-Value	Std Error	Coef	P-Value	Std Error	Coef	P-Value	Std Error
Independent Variables	Male	-0.19	0.52	0.29	-0.44	0.14	0.30	-0.25	0.38	0.29
	Top University	0.04	0.85	0.22	0.15	0.51	0.23	-0.05	0.80	0.22
	Age	-0.02	0.00	0.01	-0.02	0.00	0.01	-0.02	0.00	0.01

n = 183

Appendix F

Table 29 - Correlation Matrix of All Variables

Others	**Bs**	**Investments**	**Exits**	**Top Investments**	**Top Exits**	**Top List**	**Age**	**Top University**	**Sciences**	**Management**	**Ms**	**MBA**	**PhD**	**Male**	
-0.090	-0.043	-0.014	-0.008	0.010	-0.007	0.009	0.177	0.040	0.044	0.046	-0.009	0.054	-0.010	1.000	**Male**
0.045	-0.211	0.012	0.022	0.007	-0.014	0.010	0.078	0.083	0.243	-0.217	-0.051	-0.150	1.000	-0.010	**PhD**
-0.419	-0.814	-0.009	0.028	-0.011	0.050	-0.024	0.156	0.241	-0.317	0.597	-0.196	1.000	-0.150	0.054	**MBA**
0.041	-0.276	0.037	0.038	0.043	0.025	0.023	0.062	-0.024	0.222	-0.197	1.000	-0.196	-0.051	-0.009	**Ms**
-0.703	-0.398	-0.037	-0.006	-0.044	0.002	-0.054	-0.002	0.056	-0.531	1.000	-0.197	0.597	-0.217	0.046	**Management**
-0.229	0.106	0.085	0.079	0.095	0.060	0.103	0.000	-0.002	1.000	-0.531	0.222	-0.317	0.243	0.044	**Sciences**
-0.062	-0.253	0.083	0.115	0.079	0.090	0.077	-0.006	1.000	-0.002	0.056	-0.024	0.241	0.083	0.040	**Top University**
0.002	-0.210	-0.039	-0.009	-0.028	-0.014	-0.027	1.000	-0.006	0.000	-0.002	0.062	0.156	0.078	0.177	**Age**
-0.025	0.008	0.608	0.668	0.665	0.575	1.000	-0.027	0.077	0.103	-0.054	0.023	-0.024	0.010	0.009	**Top List**
-0.053	-0.055	0.743	0.813	0.814	1.000	0.575	-0.014	0.090	0.060	0.002	0.025	0.050	-0.014	-0.007	**Top Exits**
-0.030	-0.012	0.824	0.787	1.000	0.814	0.665	-0.028	0.079	0.095	-0.044	0.043	-0.011	0.007	0.010	**Top Investments**
-0.059	-0.054	0.912	1.000	0.787	0.813	0.668	-0.009	0.115	0.079	-0.006	0.038	0.028	0.022	-0.008	**Exits**
-0.030	-0.014	1.000	0.912	0.824	0.743	0.608	-0.039	0.083	0.085	-0.037	0.037	-0.009	0.012	-0.014	**Investments**
0.368	1.000	-0.014	-0.054	-0.012	-0.055	0.008	-0.210	-0.253	0.106	-0.398	-0.276	-0.814	-0.211	-0.043	**Bs**
1.000	0.368	-0.030	-0.059	-0.030	-0.053	-0.025	0.002	-0.062	-0.229	-0.703	0.041	-0.419	0.045	-0.090	**Others**

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